

T TESTS

A t-test compares two distributions to test the null hypothesis that the two means are not different. t-Tests are classic, related to ANOVAs, and still legit for simple comparisons. Here we explore a number of binary (two condition) potential drivers of birth weights in North Carolina.

In 2004, the state of North Carolina released a large data set containing information on births recorded there. This data set is useful to researchers studying predictors of newborn weights, which itself predicts health. We will test the following three hypotheses:

- # A. Smoking by pregnant women causes their newborn babies to weigh less at birth than babies born to mothers who do not smoke. This would support efforts to reduce smoking.
- # B. Babies born to married women weigh more on average than those born to unmarried mothers (note that same-sex marriage was not legal in NC in 2004). This would support need-based prenatal programs (where single- vs. dual income is assumed to affect access to health care, etc.).
- # C. Babies born to white mothers weigh more on average than those born to non-white mothers. This would support prenatal programs in minority-dominated areas to improve newborn health (because race remains a proxy for economic disadvantages, health care access, etc.).

Notice that we focus on quantitative responses to categorical predictors.

Load the ncbirths data set, then attach it for convenience, and view it. Variables are:

- # fage = father's age
- # mage = mother's age
- # mature = category for mother's age
- # weeks = pregnancy interval
- # premie = category for weeks
- # visits = number of prenatal doctor visits
- # marital = legal marital status
- # gained = weight gained while pregnant (lbs)
- # weight = baby's weight at delivery (lbs)
- # lowbirthweight = category for weight
- # gender = baby's sex
- # habit = mother is smoker or not
- # whitemom = mother is white or not

summary(ncbirths) # to inspect the data - any problems with the data columns we will use?

What to do with NAs? - include this line in commands below: na.rm=TRUE
this essentially says "NA removal = true" and omits NAs from analyses

Assumptions

Do the data we use here (weights) fit assumptions of normality [and homogeneous variance]

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# for each comparison we will make (habit, marital, whitemom)?
# If not, make data fit assumptions using transformations, as you already learned to do.

# Here's the scoop on t-tests. Unlike some statistical packages, the default assumes unequal
# variance (convenient!) and applies the Welsh df modification. The basic commands are:

# independent 2-group t-test
t.test(y~x) # where y is numeric and x is a binary factor

# independent 2-group t-test
t.test(y1,y2) # where y1 and y2 are numeric

# paired t-test
t.test(y1,y2,paired=TRUE) # where y1 & y2 are numeric

# one sample t-test
t.test(y,mu=0) # Ho: mu=0

# options include:
# the var.equal = TRUE statement, inside (), to specify equal variances
# the alternative="less" or alternative="greater" option to specify a one tailed test, as opposed
# to the default alternative="two.sided". Notice that the order of subtraction for that option is
# alphabetical (e.g., nonsmoker – smoker).

# Now test the three hypotheses using t-tests, where YOU CHOOSE appropriately among the
options above.

# Try one more hypothesis that you make up.

# One last consideration: we have now tried (at least) 4 different t-tests on birth weight. With
# enough attempts, we might eventually stumble on a significant effect at random. Thus a
# Bonferroni correction: where we adjust the critical p-value to find significance for the number
# of t-tests we conduct.

# So if we stick to just the three hypotheses (A-C), the Bonferonni correction would lead to a
# critical p-vale of  $0.05 / 3 = 0.0167$ . Thus any one test would have to attain a p-value of 0.0167
# or less to be considered significant, rather than the customary 0.05. Did this change any of your
# interpretations?
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